**Kant:**

**Side effect**

**Do more than expected**

**Consequentialism**

**Result is not good**

**Overall utility is accepted?**

**Dilemma**

**Advanced algo:**

**Efficiency**

**Potential accuracy**

**Data variety**

**Drawback:**

**Monitoring**

**Information depth**

**Too many sensitive/private info?**

**Measurement**

**Facial recognition and so on**

**Purpose**

**Only HR algo?**

**Usefulness?**

**Overfitting**

**Transparency and predictability**

**More reliable database**

**Some users reject to provide**

<https://www.brookings.edu/research/fairness-in-algorithmic-decision-making/>

Key word:

**Fairness**

Find non-obvious patterns and factors to improve accuracy and fairness.

With more factors, pool of qualified applicants can be expanded so that the diversity is improved as a result.

**Bias**

**Hidden biases**

Bias from the database may produce discriminatory decisions.

Dataset may underrepresent members of protected classes.

**Law**

Illegal discrimination can be intentional and unconscious. When neutral procedure disproportionately and systematically harm protected classes

**Uncontrollable**

Even if developers deliberately avoid using variables for protected classes, [automated decision] systems can still produce a disparate impact

**Hidden**

The impact is not clear/hard to find.

**Dataset**

Accuracy and fairness depend on adequate dataset.

How to get/examine/revise.

Other arguments:

**Acceptable level?**

Save lots of time/money, what is maximum compromise? No?

<https://link.springer.com/article/10.1007/s10551-019-04204-w>

**Profound effect on employees, especially integrity**

**Found in preface**

In this paper, we analyze how algorithm-based HR decision-making (i.e., algorithms designed to support and govern HR decisions), may influence employees’ personal integrity, defined as a person’s consistency between convictions, words, and actions (Palanski and Yammarino 2009). As Margolis et al. (2007, p. 237) put it, HR management has “the potential to change, shape, redirect and fundamentally alter the course of other people’s lives.

**Integrity**

Shift balance between integrity and compliance

Process, rules. Marginalize human sense-making as part of decision making process.

The concept of personal integrity is pivotal to our examination; it can be defined as an individual’s consistency between convictions, words, and actions (Palanski and Yammarino 2009).

**Monitoring**

collection and use of data on employee activities in order to facilitate their management

the line between monitoring employees at the workplace and in private has increasingly become blurred

**spill-over effects on employees’ private lives**

Yet, current algorithm-based HR decision-making tools go far beyond the monitoring activities described in the electronic monitoring literature (Ananny 2016; Dourish 2016; Seaver 2017).

**Limitation**

Side effect:

However, we suggest that while algorithm-based HR decision-making aggravates some of the already known quandaries, it also creates **novel tensions**, such as increased **information asymmetries** between management and employees, thereby reducing employees’ sense of **autonomy**

**Lack of capacity of moral imagination** (to be aware of contextual moral dilemmas and to create new solutions)

**Inflexible**

**diminishing opportunities for human sense-making**

Furthermore, Lee (2018) found in an experiment that when recruitment decisions and performance evaluations are made by an algorithm they are less likely to be perceived as fair and trustworthy, while simultaneously evoking more negative emotions than human decisions.

Flexible ethics

**Blind Trust in Rules**

**Amplifies the misclassification/prediction**

**tendency to rely on technology** in situations where reflexivity would be needed

Different value, the context is varying, for same event, the decision may vary.

Fail to detect errors, need more human sense.

**Objectivity and Neutrality**

Too numeric/quantitative

Compliance mechanism

**Scope**

algorithm-based HR decision-making is embedded in a particular “worldview” (Lowrie 2017; Zuboff 2015) related to its makers and funders

**Code represents culture background/subconsciousness**

Algorithms reflect the norms and values of its makers and funders (Crawford 2013a; Hallinan and Striphas 2014; Jasanoff 2016)

Problem solving instead of philosophical pros and cons

According to Morozov (2013, p. 1), the culture of Silicon Valley reflects an “intellectual pathology that recognizes problems as problems based on just one criterion: whether they are ‘solvable’ with a nice and clean technological solution … and not because we’ve weighed all the philosophical pros and cons.”

**Technology failure may harm neutrality**

**Transparency**

Hard to control, measure, predict

But with increasing analytical power, these algorithms also become more opaque regarding their underlying hidden assumptions

Algorithms in the context of HR decision-making are typically black boxes based on proprietary code that technology companies are not willing to share with the public (Burrell 2016; Pasquale 2015). This lack of transparency makes it difficult for HR managers to uncover biases either in the code of an algorithm itself or in the data with which the algorithm was trained (Martin 2018).

**Unexpected result**

**Predictive discrimination**

Filter target audience for recruiting ads

**Technological discrimination**

Technology works well on some groups

**Code represents culture background/subconsciousness**

**Other**

**Integrity explanation**

In her seminal paper, Paine (1994) defines integrity as a “concept of self-governance in accordance with a set of guiding principles.” Integrity is often contrasted with compliance. Compliance is organizationally governed behavior, i.e., making employees conform to (organizational) standards and rules by means of monitoring as well as by sanctioning and incentivizing rule conformity.

**Flexible ethics**

Hence, according to discourse ethics these aspects of morality are difficult to prescribe because most values are context depended and “the validity of moral claims cannot be justified by an isolated individual reflecting monologically upon the world

<https://link.springer.com/article/10.1007/s40685-020-00134-w>

**Keywords:**

**Review (accountability)**

Complicating this issue, biases and discrimination are often only recognized after algorithms have made a decision

the hiring algorithms applied by the American e-commerce specialist Amazon yielded an extreme disadvantage of female applicants, which finally led Amazon to shut down the complete algorithmic decision-making for their hiring decision (Dastin 2018; Miller 2015)

**others**

**Accepted level**

Previous studies showed that applicants’ and employees’ acceptance of algorithmic decision-making is lower in HR recruitment and HR development compared to common procedures conducted by humans (Kaibel et al. 2019; Langer et al. 2019; Lee 2018).

**Bias**

**Representative bias**

Another reason for biases in algorithms related to the input data is that certain groups or characteristics are mostly underrepresented or sometimes overrepresented, which is also called representation bias

**Technical bias**

Human constructs, such as judgments or intuitions, are often hard to quantify, which makes it difficult or even impossible to translate them to the computer (Friedman and Nissenbaum 1996). As an example, the human interpretation of law can be ambiguous and highly dependent on the specific context, making it difficult for an algorithmic system to correctly advise in litigation (c.f., Friedman and Nissenbaum 1996).

**Emergent bias**

Typically, this bias occurs after the construction as a result of changed societal knowledge, population, or cultural values (Friedman and Nissenbaum 1996).

for example, when users originate from a cultural context that avoids competition and promotes cooperative efforts, while the algorithm is trained to reward individualistic and competitive behavior (Friedman and Nissenbaum 1996).